IJMS 11 (SPECIAL ISSUE), 129-155 (2004)

DO ASIAN STOCK MARKET PRICES FOLLOW RANDOM WALK? A REVISIT

KIAN-PING LIM
Labuan School of International Business and Finance
Universiti Malaysia Sabah

MUZAFAR SHAH HABIBULLAH
Faculty of Economics and Management
Universiti Putra Malaysia

HOCK-ANN LEE
Labuan School of International Business and Finance
Universiti Malaysia Sabah

ABSTRACT

This study re-examines the price behaviour of Asian stock markets in light of the random walk hypothesis. With a new statistical tool, namely the Brock-Dechert-Scheinkman (BDS) test, it is possible for researchers to detect more complex form of dependencies in series of financial returns that often appear completely random to standard statistical tests, such as serial correlation tests, runs test, variance ratio test and unit root tests. Our results suggest that all the returns series in general do not follow a random walk process. This conclusion holds in both sub-periods (pre- and post-crisis) for Bangkok S.E.T. (BSET), Jakarta SE Composite (JSE), Kuala Lumpur SE Composite (KLSE), Korea SE Composite (KSE), and the Philippines SE Composite (PSE). For Hong Kong Hang-Seng (HKHS), the empirical results support our conjecture that the Asian financial crisis in 1997 adversely affected the market's ability to price stocks efficiently, thus preventing stock prices from following a random walk process. In particular, the price behaviour of this market experienced a dramatic change from random walk in the pre-crisis period to non-random during the crisis.

Keywords: *Random walk, weak-form efficiency, BDS test, Asian Stock Markets.*

ABSTRAK

Kajian ini meneliti semula tindak balas harga pasaran saham di Asia dalam konteks hipotesis pergerakan rawak. Dengan menggunakan alat statistik baru iaitu ujian Brock-Dechert-Scheinkman (BDS), penyelidik dapat mengesan bentuk perkaitan yang lebih kompleks di antara siri pulangan kewangan yang selalunya dianggap rawak hasil daripada ujian statistik yang standard, seperti ujian korelasi bersiri, 'runs test', ujian nisbah varians dan ujian punca satu. Hasil kajian mencadangkan bahawa semua siri pulangan secara amnya tidak mengikut proses pergerakan rawak. Keadaan ini wujud untuk kedua-dua tempoh (sebelum dan selepas krisis) untuk Bangkok S.E.T. (BSET), Jakarta SE Composite (JSE), Kuala Lumpur SE Composite (KLSE), Korea SE Composite (KSE), dan Philippines SE Composite (PSE). Dalam kes Hong Kong Hang-Seng (HKHS), hasil empirikal menyokong tekaan bahawa krisis kewangan di Asia pada tahun 1997 akan menjejaskan keupayaan pasaran untuk menetapkan harga secara cekap, seterusnya menghalang harga saham daripada mengikut proses pergerakan rawak. Pada khususnya, tindak balas harga pasaran tersebut mengalami perubahan dramatik daripada pergerakan rawak sebelum krisis kepada tak-rawak semasa krisis.

Kata kunci: *Pergerakan rawak, kecekapan bentuk lemah, Ujian BDS, Pasaran Saham Asia.*

INTRODUCTION

In the early treatments of the efficient market hypothesis, the statement that the current price of a security reflects all available information is assumed to imply that successive price changes are independent. Furthermore, it is usually assumed that successive price changes are identically distributed. Together, these two hypotheses constitute the cornerstone of the random walk model (Fama, 1965).

Formally, the random walk model can be stated as:

$$p_t = p_{t-1} + \mu_t \tag{1}$$

where p_t is the price at time t, p_{t-1} is the price in the immediate preceding period and μ_t is a random error term. A purely random process is what statisticians called 'independent and identical distribution' (i.i.d.), such as a Gaussian with zero mean and constant variance. The price change, $\Delta p_t = p_t - p_{t-1}$, is simply μ_t which being white noise, is unpredictable from previous price changes. Looking from a different perspective, equation (1) states that the best forecast of the price of a security at time t+1 is the price at time t, which in turn implies that the expected gain or loss for any holding period is zero. Therefore, analysis of past prices is meaningless because patterns observed in the past occurred purely by chance. Annuar and Shamsher (1993), Yong (1993a) and Campbell, Lo & MacKinlay (1997), amongst others, have provided excellent reviews on the subject of random walk.

Since the stock market is one of the leading economic indicators, there has been an explosion of empirical research on the behaviour of stock prices, especially in the framework of random walk hypothesis. The motivation for this line of inquiry is threefold.

First, most asset pricing models often assume that asset prices are independent and identically distributed (i.i.d.), such as the mean-variance model, Capital Asset Pricing Model (CAPM) and Black-Scholes option pricing model. Even the statistical tests of the models require the i.i.d. assumption for their asymptotic validity. Thus, for valid inferences to be made, this assumption of i.i.d. must be satisfied. Second, most empirical studies hypothesize random walk behaviour to test for the informational efficiency of stock markets. In particular, a random walk series implies that the market is weak-form efficient. Since new information is deemed to come in a random fashion in an efficient market, changes in prices that occur as a consequence of that information will seem random. Thus, investors in weak-form efficient market cannot expect to find any patterns in the historical sequence of stock prices that will provide insight into future price movements and allow them to earn abnormal rates of returns. However, if the hypothesis of random walk is rejected, it will be a strong statement to conclude that the market is inefficient[1]. As noted by Ko and Lee (1991, p.224), "*If the random walk hypothesis holds, the weak form of the efficient market hypothesis must hold, but not vice versa. Thus, evidence supporting the random walk model is the evidence of market efficiency. But violation of the random walk model need not be evidence of market inefficiency in the weak form*". The third implication, which follows from the second, is that if stock prices behave randomly, then this poses a major challenge to market analysts who employ time series modelling and technical analysts who believe that history tends to repeat itself, to the extent of implying that their work is of no real value to the stock market investors[2]. Even to proponents of fundamental analysis, the implication is no lesser. The justification is that if the random walk theory is valid, stock prices at any point in time will represent good estimates of the intrinsic or fundamental values. In this regard, additional fundamental analysis is of value only when the analyst can predict the appearance of new information that was not fully considered in forming current market prices and to evaluate its impact on the intrinsic values. Without that, it would be better to choose securities by a random selection procedure.

The body of literature on random walk can be considered as one of the richest, covering both developed and emerging financial markets, and it is practically impossible for us to review all of them in this paper. Generally, earlier studies have tested whether stock prices follow a random walk by using serial correlation tests, runs test, variance ratio test and unit root tests (see, for example, Fama, 1965, 1976; Cooper, 1982; Fama & French, 1988; Lo & MacKinlay, 1988; Lee, 1992; Zhu, 1998). A survey of the literature disclosed that studies on Asian stock markets have applied similar methodologies (see, for example, Ang & Pohlman, 1978; Hong, 1978; D'Ambrosio, 1980; Wong & Kwong, 1984; Barnes, 1986; Laurence, 1986; Yong, 1989, 1990, 1993b; Annuar, Ariff & Shamsher, 1991, 1993; Annuar & Shamsher, 1993; Ayadi & Pyun, 1994; Kok & Lee, 1994; Kok & Goh, 1995; Fawson, Glover, Fang & Chang, 1996; Poshakwale, 1996; Laurence, Cai & Qian, 1997; Mookerjee & Yu, 1999; Cheung & Coutts, 2001; Chaudhuri & Wu, 2003).

However, there are some common shortcomings associated with the above cited literature. In particular, the application of the standard statistical tests to examine the random walk behaviour of financial time series has been challenged in recent times by the development of new non-linear statistical tests. Most of these studies focused only on testing the first hypothesis that successive price changes are independent of one another, partly due to the limitations of the methodologies employed. In this regard, they are not testing the strongest version of random walk[3]. On the other hand, in testing for independence, the standard statistical tests employed are designed to uncover linear dependencies in the data. However, the lack of linear dependencies does not imply that the series are random as there might be other more complex forms of dependencies which cannot be detected by these standard methodologies. Even Fama (1965, p.80) admitted that linear modelling techniques have limitations, as they are not sophisticated enough to capture complicated 'patterns' that the chartist sees in stock prices. Steurer (1995, p.202) expressed a similar opinion, in which he argued that there is an order to the apparent randomness of the market. This order is so complex that the random walk concept is proven by the standard linear statistical tests. Another researcher, Brooks (1996, p.307) agreed that series of financial returns often appear completely random to standard linear and spectral tests. However, he strongly believed that with a different approach, using more powerful techniques, it may be possible to uncover a more complex form of dependencies in these series.

One of the possibilities that might contribute to the departure from random walk is the presence of non-linear dependencies in the underlying data generating process. Indeed, it is widely acknowledged that non-linear dependencies is a new-found salient feature of most financial time series (see, for example, Hsieh, 1989, 1991; Scheinkman & LeBaron, 1989; De Grauwe, Dewachter & Embrechts, 1993; Abhyankar, Copeland & Wong, 1995; Steurer, 1995; Brooks, 1996; Barkoulas & Travlos, 1998; Opong, Mulholland, Fox & Farahmand, 1999). This evidence of non-linearity has strong implication on the efficient market hypothesis for it implies the potential of returns predictability. Specifically, if investors could have profitably operated a trading rule (net of all transactions costs) that exploits this detected non-linearity, it would be at odds with the weak-form efficient market hypothesis, which postulated that even non-linear combinations of previous prices are not useful predictors of future prices (Brooks, 1996; Brooks & Hinich, 1999; McMillan & Speight, 2001). However, the standard statistical tests such as serial correlation tests, runs test, variance ratio test and unit root tests may fail to detect non-linear departure from the random walk hypothesis (Hsieh, 1989). Thus, there is a need for researchers to re-examine earlier observed series that appeared random to standard linear statistical tests to avoid making incorrect inferences and misleading policy guidelines. As pointed out by Liew, Chong & Lim (2003), failure to account for non-linearity can produce misleading tests and result in incorrect inferences.

Recent breakthroughs pertaining to non-linear dynamics, coupled with the rapid acceleration in computer power, have made it possible to more robustly test for the random walk hypothesis. Interest in these new non-linear techniques is based on the assumption that highly complex behaviour that appears to be random is actually generated by an underlying non-linear process. Most of the recent empirical studies in the literature have extensively applied the Brock-Dechert & Scheinkman test (henceforth denoted as BDS test), developed in Brock, Dechert, Scheinkman (1987), and Brock, Dechert, Scheinkman & LeBaron (1996)[4], to test whether financial and economic time series are random walk with the property of being independent and identically distributed (see, for example, Hsieh, 1989, 1991; Scheinkman & LeBaron, 1989; De Grauwe *et al.*, 1993; Steurer, 1995; Brooks, 1996; Al-Loughani & Chappell, 1997; Mahajan & Wagner, 1999; Opong *et al.*, 1999; Serletis & Shintani, 2003). The BDS test has been proven to be quite powerful in detecting departures from i.i.d. behaviour in some

Monte Carlo simulations (see, for example, Brock, Hsieh & LeBaron, 1991; Hsieh, 1991). Specifically, the BDS test has good power to detect at least four types of non-i.i.d. behaviour: non-stationarity, linear dependencies, non-linear stochastic process and non-linear deterministic process.

Briefly, the BDS test uses the correlation integral to provide a direct test for the null hypothesis of independent and identical distribution (i.i.d.). In principle, no distributional assumption on the underlying data generating process is needed in using the BDS test as a test statistic for i.i.d. random variables. Though the estimation is non-parametric, the test statistic is asymptotically distributed as a standard normal variable, with zero mean and unit variance. Hence, the significance of the test statistic is readily determined from standard normal tables.

The main objective of this paper is to re-examine the random walk behaviour of stock prices in the context of Asian stock markets, utilizing the BDS test developed in Brock *et al.* (1987, 1996). The application to these markets is certainly worth investigating since there is a void in the current literature. From our literature survey, most of the applications on stock markets were on developed countries, such as U.S. (Scheinkman & LeBaron, 1989; Hsieh, 1991; Serletis & Shintani, 2003) and U.K. (Al-Loughani & Chappell, 1997; Opong *et al.*, 1999). Thus, the major contribution of this paper is to broaden the existing rich literature on random walk using robust econometric techniques to include the Asian stock markets, which are gaining more attention from international investors in the wave of globalization and liberalization of financial markets.

In the following section, this paper discusses the BDS test. This is followed by a brief description of the data used in this study. Section IV presents the empirical results as well as the analysis of the findings. Finally, concluding remarks are given at the end of the paper.

BROCK-DECHERT-SCHEINKMAN (BDS) TEST

Brock, Dechert and Scheinkman (Brock *et al.*, 1987) developed a statistical test and the BDS statistic. The original BDS paper used the concept of the correlation integral[5] and transformed it into a formal test statistic which is asymptotically distributed as a normal variable under the null hypothesis of independent and identically distributed (i.i.d.) against an unspecified alternative. A revision of this original paper has been done in Brock *et al.* (1996).

The BDS test is based on the correlation integral as the test statistic. Given a sample of i.i.d. observations, $\{x_t: t = 1, 2, \ldots.., n\}$, Brock *et al.* (1987, 1996) showed that:

$$W_{m,n}(\varepsilon) = \sqrt{n}\,\frac{T_{m,n}(\varepsilon)}{V_{m,n}(\varepsilon)} \tag{2}$$

has a limiting standard normal distribution, where $W_{m,n}(\varepsilon)$ is the BDS statistic. n is the sample size, m is the embedding dimension, and the metric bound, ε, is the maximum difference between pairs of observations counted in computing the correlation integral. $T_{m,n}(\varepsilon)$ measures the difference between the dispersion of the observed data series in a number of spaces with the dispersion that an i.i.d. process would generate in these same spaces, that is $C_{m,n}(\varepsilon) - C_{1,n}(\varepsilon)^m$. $T_{m,n}(\varepsilon)$ has an asymptotic normal distribution with zero mean and variance $V^2_{m}(\varepsilon)$[6].

This BDS test has an intuitive explanation. The correlation integral $C_{m,n}(\varepsilon)$ is an estimate of the probability that the distance between any two m-histories, $x_t^m = (x_t, x_{t+1}, \ldots, x_{t+m-1})$ and $x_s^m = (x_s, x_{s+1}, \ldots\ldots, x_{s+m-1})$ of the series $\{x_t\}$ is less than ε, that is, $C_{m,n}(\varepsilon) \to \text{prob}\{|x_{t+i} - x_{s+i}| < \varepsilon$, for all $i = 0, 1, \ldots\ldots.. m\text{-}1\}$, as $n \to \infty$.

If the series $\{x_t\}$ are independent, then, for $|t\text{-}s| > m$, $C_{m,n}(\varepsilon) \to \prod_{i=0}^{m-1} \text{prob}\{|x_{t+i} - x_{s+i}| < \varepsilon\}$, as $n \to \infty$. Furthermore, if the series $\{x_t\}$ are also identically distributed, then $C_{m,n}(\varepsilon) \to C_1(\varepsilon)^m$, as $n \to \infty$. The BDS statistic therefore tests the null hypothesis that $C_{m,n}(\varepsilon) = C_{1,n}(\varepsilon)^m$, which is the null hypothesis of i.i.d [7].

The need to choose the values of ε and m can be a complication in using the BDS test. For a given m, ε cannot be too small because $C_{m,n}(\varepsilon)$ will capture too few points. On the other hand, ε cannot be too large because $C_{m,n}(\varepsilon)$ will capture too many points. For this reason, we adopted the approach used by advocates of this test. In particular, we set ε as a proportion of standard deviation of the data, σ. Hsieh & LeBaron (1988a, b) have performed a number of Monte Carlo simulation tests regarding the size of the BDS statistics under the null of i.i.d. and the alternative hypotheses. The Monte Carlo evidence showed that the 'best' choice of ε is between 0.50 and 1.50 times the standard deviation.

On the other hand, at our chosen setting of ε, we used the BDS test statistics, $W_{m,n}(\varepsilon)$ for all settings of embedding dimension from 2 to 5. Though most researchers computed the BDS statistics for embedding dimension varying from 2 to 10 (see, for example, Hsieh, 1989; De Grauwe *et al.*, 1993; Brooks, 1996; Mahajan & Wagner, 1999; Opong *et al.*, 1999), it is important to take note that the small samples properties of BDS test degrade as one increases the embedding dimension. Specifically the Monte Carlo simulations in Brock *et al.* (1991) demonstrated that as the dimension goes beyond 5, the small samples properties of BDS degrade, mainly due to the reduction of non-overlapping observations as m grows. Thus, this study only reports results with embedding dimensions of 2 to 5.

THE DATA

The random walk hypothesis was tested using individual stocks in the pioneering work of Fama (1965). According to the author, the use of market index data in random walk tests may lead to a false perception of price change dependence even when price changes of individual stocks represented by the index are independent. However, the limitations of using data of individual stocks should not be ignored. The first difficulty involves the selection of stocks to represent the market. Unless the data cover all the stocks traded on the market (see, for example, Yong 1993b), one might be subjected to criticism that the sample stocks are not quite representative of the market. The second problem lies in the assessment of market based on the empirical results of those selected individual stocks. For example, Fama (1965) upheld the theory of random walk as only 11 out of 30 stocks or 36.67% rejected the null hypothesis of zero serial correlation coefficients. On the application of runs test, 26.67% (8 out of 30 stocks) violating randomness is not, in Fama's opinion, considered to be sufficient evidence against the efficient market hypothesis. However, should one continue to use the criterion set by Fama (1965) 38 years ago as the benchmark for market assessment, as has been done in Solnik (1973) and Laurence (1986). In this regard, there is always a possibility that a small subset of stocks may lead to the false conclusion of inefficiency for the whole market.

In the literature, studies utilized indices to evaluate the random character of a particular market for the purpose of testing weak form market efficiency are no lesser (see, for example, Hong, 1978; D'Ambrosio, 1980; Lee, 1992; Annuar *et al.*, 1993; Ayadi & Pyun, 1994;

Kok & Goh, 1995; Fawson *et al.*, 1996; Poshakwale, 1996; Al-Loughani & Chappell, 1997; Laurence *et al.*, 1997; Zhu, 1998; Mookerjee & Yu, 1999; Opong *et al.*, 1999; Cheung & Coutts, 2001; Chaudhuri & Wu, 2003; Serletis & Shintani, 2003). Results from aggregate market indices have direct bearing on the trading strategies of investors, particularly institutional investors with diversified portfolios, whose fortunes may move in tandem with the market average (Kok & Goh 1995, p.76; Hong, 1978, p.619). Moreover, as pointed out by Opong *et al.* (1999) that the behaviour of market indices is of major importance in the pricing of derivatives traded on them.

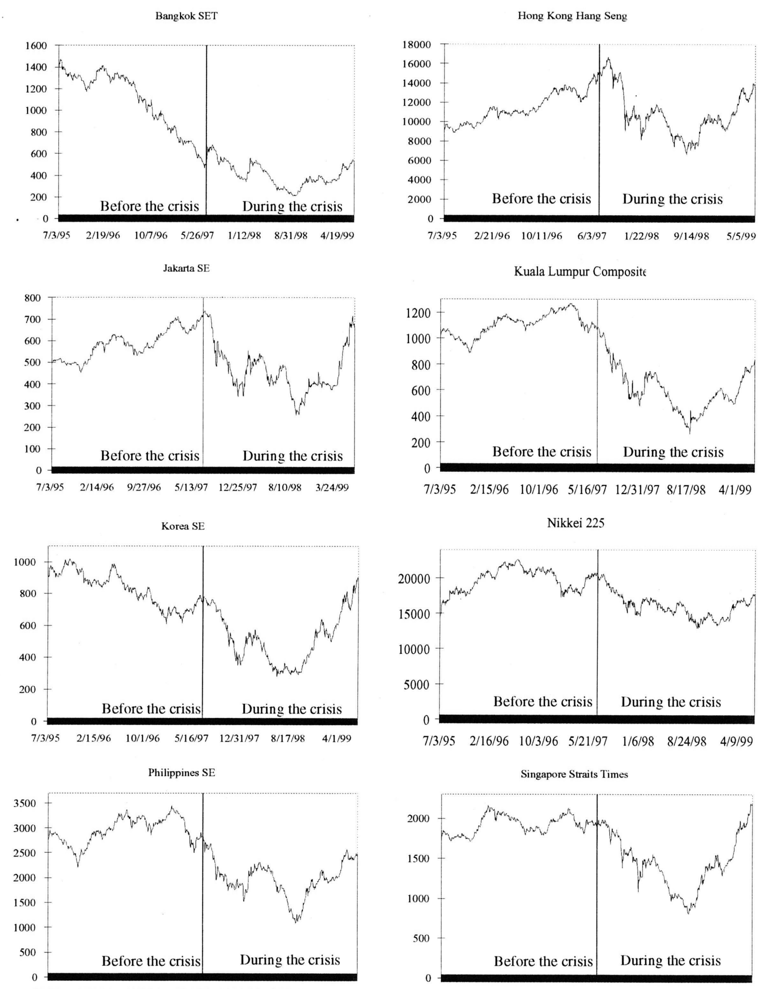

Figure 1
Major Indices of Asian Stock Markets

Thus, this study re-examines the random walk behaviour of stock prices in eight major Asian stock markets using market indices. The data consist of daily closing prices for the following market indices: Bangkok S.E.T. (Thailand), Hang-Seng (Hong Kong), Jakarta SE Composite (Indonesia), Kuala Lumpur SE Composite (Malaysia), Korea SE Composite (South Korea), Nikkei 225 Stock Average (Japan), Philippines SE Composite (the Philippines) and Singapore Straits Times (Singapore). All the data are collected from *Datastream*. The indices are denominated in their respective local currency units and the graphical plots are shown in Figure 1.

The prices covering the sample period from 1 July 1995 to 30 June 1999 are transformed into a series of continuously compounded percentage returns, using the relationship:

$$r_t = 100^* \ln(p_t / p_{t-1}) \tag{3}$$

where p_t is the closing price of the stock on day t, and p_{t-1} the price on the previous trading day.

In this study, we test the random walk hypothesis over the whole sample. To observe the consistency of the results, the study period for each index series is then broken down into two sub-periods with equal length for separate BDS test [8]. The first sub-period is from 1 July 1995 through 30 June 1997 while the second period runs from 1 July 1997 through 30 June 1999, with the Asian financial crisis as the break point. The main consideration in determining the length of each sub-period is to ensure enough observations for the BDS statistic to have limiting normal distribution under the null of i.i.d. Specifically, the Monte Carlo simulations in Brock *et al.* (1991) suggested that the asymptotic distribution can approximate the finite sample distribution of the BDS statistic for 500 or more observations.

The motivation for this sub-periods analysis is twofold. One, it is possible to determine whether the rejection of the random walk in the full sample is driven by the behaviour of stock prices in any particular sub-period. Similarly, the inability to reject random walk for the full sample could have masked significant result in any sub-period. Second, it would be interesting to compare the behaviour of stock prices before and during a financial crisis, an area which has not been well-researched in the literature. It is well acknowledged that the economic and financial turmoil that struck Asia in July 1997 was representative of both crisis and panic. What appeared to be a local financial crisis in Thailand quickly escalated into an Asian financial crisis, spreading to other Asian countries like Indonesia, Korea, Malaysia and the Philippines. We conjecture that the crisis might have contributed to the non-random behaviour of stock prices as these panic investors were not able to make a rational assessment of the market and adjust rapidly and unbiasedly to the arrival of new information.

EMPIRICAL RESULTS

Table 1 provides summary statistics for all the Asian stock returns series under study. The means are quite small. All of the returns series exhibit some degree of positive or right-skewness. On the other hand, the distributions for all the series are highly leptokurtic, in which the tails of their respective distributions taper down to zero more gradually than do the tails of a normal distribution. Not surprisingly, given the non-zero skewness levels and excess kurtosis demonstrated within these series of returns, the Jarque-Bera (JB) test strongly rejects the null of normality.

Subsequently, we apply the BDS test on all the Asian stock returns series in order to test whether these returns series are random walk with the property of being independent and identically distributed. All the BDS statistics, $W_{m,n}(\varepsilon)$, are computed in *EViews* version 4.1, for all combinations of m and ε where $m = 2, 3, \ldots\ldots 5$ and $\varepsilon = 0.50\sigma, 0.75\sigma, 1.00\sigma, 1.25\sigma$ and 1.50σ. Though most researchers reported results with embedding dimensions varying from 2 to 10, this study gives serious consideration to the results with embedding dimensions of 2 to 5. As mentioned earlier, the Monte Carlo simulations in Brock *et al.* (1991) demonstrated that as the dimension goes beyond 5, the small samples properties of BDS degrade, mainly due to the reduction of non-overlapping observations as m grows. On the other hand, though our sample sizes have sufficient observations for the asymptotic normal distribution, including those in the sub-periods analysis, we have computed the bootstrapped p-values for the BDS statistics with 10000 repetitions, an option given in *EViews* 4.1, to ensure the robustness of the results.

First, we test the random walk hypothesis over the full sample period and the results are reported in Table 2. It is obvious that all the BDS statistics are in the extreme positive tail of the standard normal distribution. The positive values show that there is more clustering of points in m-dimensional space than would be expected in a true random series. On the other hand, negative BDS statistics indicate that certain patterns are too infrequent. However, only significant BDS statistics, both positive and negative, are indications of non-i.i.d. behaviour. The bootstrapped p-values given in parentheses show

Table 1
Summary Statistics

	BSET	HKHS	JSE	KLSE	KSE	NIKKEI	PSE	SST
Sample Period	1/7/1995 30/6/1999	1/7/1995 30/6/1999	1/7/1995 30/6/1999	1/7/1995 30/6/1999	1/7/1995 30/6/1999	1/7/1995 30/6/1999	1/7/1995 30/6/1999	1/7/1995 30/6/1999
No. of observations	1042	1042	1042	1042	1042	1042	1042	1042
Mean	-0.093347	0.037678	0.028470	-0.022323	-0.003322	0.018307	-0.010285	0.019432
Median	-0.138522	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Maximum	11.34953	17.24710	13.12768	20.81737	10.02377	7.660481	9.665750	14.86849
Minimum	-10.02803	-14.73468	-12.73213	-24.15339	-11.60062	-5.957070	-9.744158	-9.671880
Std deviation	2.129966	2.021790	2.062822	2.332660	2.298061	1.448715	1.746227	1.623778
Skewness	0.918512	0.312645	0.327798	0.600610	0.265020	0.211642	0.070168	0.836874
Kurtosis	7.202303	14.92674	10.56721	30.40136	6.306763	5.572195	7.749200	15.28097
JB normality test statistic	913.2267	6192.870	2504.818	32661.38	486.9449	295.0317	980.1135	6669.829
(*p*-value)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)

Note: BSET- Bangkok S.E.T.; HKHS- Hong Kong Hang-Seng; JSE- Jakarta SE Composite; KLSE- Kuala Lumpur SE Composite; KSE- Korea SE Composite; NIKKEI- Nikkei 225 Stock Average; PSE- Philippines SE Composite; SST- Singapore Straits Times.

that all the BDS statistics are significant even at the 1% level, suggesting that all the returns series behave non-randomly. According to Brock *et al.* (1991), the large BDS statistics can arise in two ways. It can either be that the finite sample distribution under the null of i.i.d. is poorly approximated by the asymptotic normal distribution, or the BDS statistics are large when the null hypothesis of i.i.d. is violated. From the various Monte Carlo simulations, Brock *et al.* (1991) ruled out the first possibility, thus suggesting that our large BDS statistics in Table 2 provide strong evidence of departure from the i.i.d. null.

To observe the consistency of the results, the study period for each index series is broken down into two sub-periods with equal length for separate BDS test. The results are reported in Table 3 (period before the crisis) and Table 4 (period during the crisis) respectively. The comparison reveals that the rejection of the null of i.i.d. is consistent in both sub-periods for Bangkok S.E.T. (BSET), Jakarta SE Composite (JSE), Kuala Lumpur SE Composite (KLSE), Korea SE Composite (KSE), and the Philippines SE Composite (PSE). These consistent BDS results provide strong evidence that the price behaviour in the above five Asian stock markets do not follow a random walk movement. However, as cautioned by Ko & Lee (1991), it would be a strong statement to conclude that these markets are inefficient in the weak form.

Another interesting insight comes from the Nikkei 225 Stock Average (Nikkei). Though the null is strongly rejected in the full sample, a closer examination using sub-periods analysis reveals that there are pockets of efficiency in which the Nikkei returns series behave randomly at lower ε and this result is consistent in both sub-periods. No explanation is offered at this stage as it requires extensive study to substantiate our claim.

The sub-periods analysis not only serves to determine the consistency of the BDS results, it does provide meaningful comparison. We have earlier justified the selection of July 1 1997 as the break point. This study postulates that the period during crisis might contribute to the non-random price behaviour since it is well acknowledged that the 1997 Asian financial crisis was representative of crisis and panic. In particular, it is widely believed that investors acted upon rumours rather than credible information and this adversely affected the market's ability to price stocks efficiently. The results in Table 4 clearly demonstrate that all the stock returns behave non-randomly during the crisis period, with the exception of the Nikkei, with pockets of efficiency at lower ε.

However, the empirical support for our conjecture that the Asian financial crisis did indeed prevent stock prices from following a random walk process comes from Singapore Straits Times (SST) and Hong Kong Hang-Seng (HKHS). For the case of Singapore Straits Times, there are pockets of efficiency before the crisis at $\varepsilon = 0.50\sigma$. This evidence of efficiency disappears in the crisis period as all the BDS statistics are significant, suggesting that the crisis has contributed to the full divergence of SST from random walk. The Hong Kong Hang-Seng, on the other hand, offers the strongest support as we observe a dramatic change in the price behaviour from one period to another. The bootstrapped *p*-values suggest that the null of i.i.d. cannot be rejected even at the 10% level in the pre-crisis period, which implies that the market is weak-form efficient. It is important to note that the evidence of random walk is robust since the BDS test was proven to be quite powerful in detecting departure from random walk. However, as a result of the financial crisis, the behaviour of the HKHS returns series experience a dramatic shift from random walk to non-random, as shown in Table 4 where all the BDS statistics can reject the null at 10% level. This result also reveals that the rejection of the random walk in the full sample is actually driven by the behaviour of HKHS returns series in the crisis period.

CONCLUSIONS

This study re-examines the price behaviour of Asian stock markets in light of the random walk hypothesis. With a new and powerful statistical tool, namely the BDS test, it is possible to detect a more complex form of dependencies in series of financial returns that often appear completely random to standard statistical tests, such as serial correlation tests, non-parametric runs test, variance ratio test and unit root tests. Our econometric investigations reveal that all the returns series in general do not follow a random walk process. This conclusion holds even when the sample period is broken down into sub-periods for Bangkok S.E.T. (BSET), Jakarta SE Composite (JSE), Kuala Lumpur SE Composite (KLSE), Korea SE Composite (KSE), and the Philippines SE Composite (PSE).

However, it would be a strong statement to conclude that the above markets are inefficient in the weak form, unless the underlying patterns of these non-random returns series can be identified and profitably exploited. Specifically, it is necessary to first investigate the causes of rejection of the i.i.d. random behaviour by the BDS test, and thenproceed to assess whether investors could have profitably operated

Table 2
BDS Test Results on Asian Stock Markets Returns Series (Full Sample)

ε	m	BSET	HKHS	JSE	KLSE	KSE	NIKKEI	PSE	SST
0.50	2	7.1222	5.5132	13.1223	11.7777	5.2561	3.0235	9.3186	10.8059
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0042)	(0.0000)	(0.0000)
	3	8.9429	6.8531	17.7050	16.4941	8.0448	3.8414	12.3980	13.8328
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0012)	(0.0000)	(0.0000)
	4	10.8338	8.5211	22.7726	21.1641	11.0711	3.7230	15.6081	16.8058
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0022)	(0.0000)	(0.0000)
	5	12.5639	10.6885	27.8509	27.9259	14.8826	4.1041	18.8698	20.2801
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0026)	(0.0000)	(0.0000)
0.75	2	7.4697	6.4646	13.2885	11.7520	6.1855	3.5359	10.0543	11.5651
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0004)	(0.0000)	(0.0000)
	3	9.2473	8.2898	16.8185	15.7245	9.2886	4.3217	12.9469	15.0235
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0000)	(0.0000)
	4	10.9414	10.1425	20.6042	19.0209	12.2582	4.2897	15.6207	17.7103
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0004)	(0.0000)	(0.0000)
	5	12.1828	12.3217	24.2826	23.0368	15.5998	4.5189	18.3871	20.4912
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0006)	(0.0000)	(0.0000)
1.00	2	7.4087	7.4991	13.1194	10.7444	6.5616	4.0232	10.2955	11.7352
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0004)	(0.0000)	(0.0000)
	3	9.2587	9.2838	15.6974	13.9976	9.7076	4.9790	12.7437	15.2551
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	4	10.7945	11.0677	18.6220	16.2752	12.5868	5.2760	14.9148	17.6860
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	5	11.8335	13.1298	21.2986	18.6038	15.4306	5.7743	17.0454	19.9216
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

(continued)

ε	m	BSET	HKHS	JSE	KLSE	KSE	NIKKEI	PSE	SST
1.25	2	7.5016	8.0569	12.9270	9.8294	6.7510	4.5347	10.3394	11.7557
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	9.2238	9.7373	14.5623	12.6233	9.7809	5.5270	12.1823	15.0153
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	4	10.5847	11.4045	16.7556	14.2206	12.4902	5.8922	13.9027	17.1926
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000
	5	11.2801	13.2719	18.7831	15.6991	14.8722	6.3743	15.4188	18.9985
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
1.50	2	7.6098	8.4690	13.0184	9.9190	6.6384	5.1077	10.2410	11.7412
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	3	9.2277	9.8414	13.9122	12.3238	9.4364	6.1589	11.7354	14.5049
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	4	10.3455	11.2591	15.5070	13.4967	11.9034	6.6596	13.2566	16.3639
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	5	10.8330	12.8016	16.9373	14.4329	13.9346	7.1730	14.4357	17.6648
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Notes: All the BDS test statistics are computed using *EViews* version 4.1. Asymptotically, the computed BDS test statistics, $W_{m,n}(\varepsilon)$ ~N(0,1) under the null of i.i.d. To compensate for smaller sample sizes, this table provides the bootstrapped p-values in parentheses, with 10000 repetitions, generated by *EViews*. The table shows that all the BDS test statistics are significant even at 1% level.

Table 3
BDS Test Results on Asian Stock Markets Returns Series (Period Before Crisis)

ε	*m*	BSET	HKHS	JSE	KLSE	KSE	NIKKEI	PSE	SST
0.50	2	4.9931	-1.5524	5.1986	3.9738	1.6377	1.4688	4.6789	1.8259
		(0.0000)*	(0.1458)	(0.0000)*	(0.0012)*	(0.1246)	(0.1570)	(0.0000)*	(0.0814)
	3	6.0707	-1.0147	7.6121	4.4838	1.7555	1.9766	5.7611	1.8150
		(0.0000)*	(0.3636)	(0.0000)*	(0.0006)*	(0.1128)	(0.0818)	(0.0000)*	(0.0992)
	4	5.9650	-0.6084	9.0795	5.2439	2.9091	1.7569	6.4383	1.3850
		(0.0002)*	(0.6306)	(0.0000)*	(0.0004)*	(0.0266)*	(0.1268)	(0.0000)*	(0.2020)
	5	6.0366	-0.0929	10.0458	6.4632	4.3132	1.7218	5.6752	1.4132
		(0.0006)*	(0.9624)	(0.0000)*	0.0004)*	0.0074)*	(0.1580)	(0.0002)*	(0.2192)
0.75	2	5.3161	-1.0933	5.3013	2.8773	2.4094	1.6589	5.3242	2.1747
		(0.0000)*	(0.3012)	(0.0000)*	(0.0084)*	(0.0286)*	(0.1084)	(0.0000)*	(0.0448)*
	3	6.4792	-0.6566	7.2035	3.4983	2.4798	2.0849	6.6403	2.4619
		(0.0000)*	(0.5824)	(0.0000)*	(0.0012)*	(0.0314)*	(0.0478)*	(0.0000)*	(0.0272)*
	4	6.6176	-0.1983	8.0324	4.0449	3.4060	1.8102	7.5582	2.6600
		(0.0000)*	(0.9426)	(0.0000)*	(0.0006)*	(0.0060)*	(0.0918)	(0.0000)*	(0.0188)*
	5	6.5709	0.0388	8.1775	4.9145	4.1181	1.9247	7.6275	3.0489
		(0.0000)*	(0.8630)	(0.0000)*	(0.0004)*	(0.0028)*	(0.0832)	(0.0000)*	(0.0134)*
1.00	2	5.5283	-0.8700	5.4718	2.3749	2.5795	2.2499	6.0524	2.6048
		(0.0000)*	(0.4174)	(0.0000)*	(0.0228)*	(0.0164)*	(0.0340)*	(0.0000)*	(0.0130)*
	3	6.6609	-0.2258	6.9072	3.1102	2.7912	2.6302	7.2600	3.1159
		(0.0000)*	(0.8966)	(0.0000)*	(0.0050)*	(0.0094)*	(0.0146)*	(0.0000)*	(0.0034)*
	4	7.0298	0.2205	7.2154	3.7075	3.7792	2.4123	7.9955	3.4856
		(0.0000)*	(0.7426)	(0.0000)*	(0.0022)*	(0.0022)*	(0.0228)*	(0.0000)*	(0.0026)*
	5	7.1753	0.2220	7.0177	4.7623	4.6611	2.5380	8.0409	3.9890
		(0.0000)*	(0.7408)	(0.0000)*	(0.0000)*	(0.0004)*	(0.0198)*	(0.0000)*	(0.0014)*

(continued)

ε	m	BSET	HKHS	JSE	KLSE	KSE	NIKKEI	PSE	SST
1.25	2	5.5538	-0.5166	5.5228	2.5452	2.7106	2.6790	6.3581	3.1170
		(0.0000)*	(0.6420)	(0.0000)*	(0.0198)*	(0.0108)*	(0.0122)*	(0.0000)*	(0.0042)*
	3	6.7640	0.2976	6.4932	3.4224	2.9892	3.0121	7.3136	3.7361
		(0.0000)*	(0.7316)	(0.0000)*	(0.0028)*	(0.0060)*	(0.0040)*	(0.0000)*	(0.0008)*
	4	7.1511	0.6917	6.5608	4.0870	4.0264	2.8231	7.8644	4.0949
		(0.0000)*	(0.4590)	(0.0000)*	(0.0008)*	(0.0006)*	(0.0090)*	(0.0000)*	(0.0002)*
	5	7.3595	0.7047	6.2180	5.0411	4.8649	2.9364	7.9720	4.5769
		(0.0000)*	(0.4480)	(0.0000)*	(0.0000)*	(0.0002)*	(0.0086)*	(0.0000)*	(0.0000)*
1.50	2	5.5192	-0.4214	5.7302	2.8819	3.0857	3.2325	6.2460	3.4938
		(0.0000)*	(0.7236)	(0.0000)*	(0.0078)*	(0.0040)*	(0.0042)*	(0.0000)*	(0.0016)*
	3	6.7529	0.5628	6.3046	3.7054	3.2927	3.5979	6.9749	4.1307
		(0.0000)*	(0.5306)	(0.0000)*	(0.0008)*	(0.0022)*	(0.0018)*	(0.0000)*	(0.0004)*
	4	7.1349	0.9716	6.2279	4.4344	4.2035	3.3209	7.4592	4.4638
		(0.0000)*	(0.3158)	(0.0000)*	(0.0002)*	(0.0002)*	(0.0048)*	(0.0000)*	(0.0002)*
	5	7.5544	1.0435	5.8611	5.2559	4.9415	3.4220	7.5491	4.8569
		(0.0000)*	(0.2818)	(0.0000)*	(0.0000)*	(0.0002)*	(0.0034)*	(0.0000)*	(0.0000)*

Notes: All the BDS test statistics are computed using *EViews* version 4.1. Asymptotically, the computed BDS test statistics, $W_{m,n}(\varepsilon)$ ~N(0,1) under the null of i.i.d. To compensate for smaller sample sizes, this table provides the bootstrapped p-values in parentheses, with 10000 repetitions, generated by *EViews*.
* denotes significant at least at the conventional 5% level.

Table 4
BDS Test Results on Asian Stock Markets Returns Series (Period During Crisis)

ε	*m*	BSET	HKHS	JSE	KLSE	KSE	NIKKEI	PSE	SST
0.50	2	2.9814	2.2314	5.9340	5.1167	1.4745	1.5487	5.2273	5.4693
		(0.0076)*	(0.0356)*	(0.0000)*	(0.0000)*	(0.1540)	(0.1388)	(0.0000)*	(0.0000)*
	3	2.9779	1.7580	7.4739	6.7776	3.0837	1.7444	6.7682	7.0280
		(0.0134)*	(0.0978)	(0.0000)*	(0.0000)*	(0.0108)*	(0.1136)	(0.0000)*	(0.0000)*
	4	2.4418	1.9167	9.7756	7.5700	4.4057	1.2952	8.2492	7.6076
		(0.0426)*	(0.0854)	(0.0000)*	(0.0000)*	(0.0020)*	(0.2236)	(0.0000)*	(0.0000)*
	5	1.6731	2.3472	12.1339	8.4150	6.0226	0.5135	9.5906	7.9954
		(0.1476)	(0.0566)	(0.0000)*	(0.0000)*	(0.0006)*	(0.5734)	(0.0000)*	(0.0000)*
0.75	2	3.3567	3.2842	6.4170	4.7622	1.6617	1.9202	5.2388	5.8262
		(0.0034)*	(0.0018)*	(0.0000)*	(0.0000)*	(0.0978)	(0.0642)	(0.0000)*	(0.0000)*
	3	3.6930	3.0877	7.0882	6.2359	2.8648	2.2282	6.3284	7.5077
		(0.0024)*	(0.0040)*	(0.0000)*	(0.0000)*	(0.0132)*	(0.0440)*	(0.0000)*	(0.0000)*
	4	3.9112	3.5635	8.7097	6.8794	4.1807	2.2549	7.4520	8.5509
		(0.0020)*	(0.0018)*	(0.0000)*	(0.0000)*	(0.0014)*	(0.0484)*	(0.0000)*	(0.0000)*
	5	3.5934	4.2593	10.2623	7.4605	5.2677	2.0657	8.4566	8.9796
		(0.0052)*	(0.0004)*	(0.0000)*	(0.0000)*	(0.0004)*	(0.0750)	(0.0000)*	(0.0000)*
1.00	2	4.0970	3.9190	7.2493	4.9651	1.6200	2.1851	5.8157	6.2995
		(0.0000)*	(0.0006)*	(0.0000)*	(0.0000)*	(0.1056)	(0.0346)*	(0.0000)*	(0.0000)*
	3	4.6747	3.9292	7.4472	6.3130	2.7126	2.5432	6.5095	7.8583
		(0.0002)*	(0.0008)*	(0.0000)*	(0.0000)*	(0.0100)*	(0.0180)*	(0.0000)*	(0.0000)*
	4	4.9419	4.3964	8.5741	6.7301	4.0937	2.6231	7.5233	8.9923
		(0.0000)*	(0.0002)*	(0.0000)*	(0.0000)*	(0.0010)*	(0.0194)*	(0.0000)*	(0.0000)*
	5	4.5296	5.0812	9.5757	7.0892	5.1261	2.6275	8.3735	9.6019
		(0.0002)*	(0.0000)*	(0.0000)*	(0.0000)*	(0.0004)*	(0.0220)*	(0.0000)*	(0.0000)*

(continued)

ε	m	BSET	HKHS	JSE	KLSE	KSE	NIKKEI	PSE	SST
1.25	2	4.8061	4.9549	7.6410	6.0559	2.0704	2.5691	5.9969	6.7538
		(0.0000)*	(0.0000)*	-(0.0000)*	(0.0000)*	(0.0492)*	(0.0166)*	(0.0000)*	(0.0000)*
	3	5.5571	5.1227	7.5751	7.3021	3.1713	3.1761	6.6103	7.8355
		(0.0000)*	(0.0000)*	(0.0000)*	(0.0000)*	(0.0044)*	(0.0038)*	(0.0000)*	(0.0000)*
	4	5.8119	5.6146	8.4305	7.7128	4.4529	3.4996	7.6690	8.8608
		(0.0000)*	(0.0000)*	(0.0000)*	(0.0000)*	(0.0004)*	(0.0022)*	(0.0000)*	(0.0000)*
	5	5.4545	6.2085	9.0946	8.0886	5.5089	3.6223	8.4164	9.4168
		(0.0000)*	(0.0000)*	(0.0000)*	(0.0000)*	(0.0000)*	(0.0028)*	(0.0000)*	(0.0000)*
1.50	2	5.4787	6.0676	7.4452	6.9766	2.6982	2.6113	5.8125	7.0749
		(0.0000)*	(0.0000)*	(0.0000)*	(0.0000)*	(0.0114)*	(0.0142)*	(0.0000)*	(0.0000)*
	3	6.3026	6.2971	7.3788	8.0245	3.5439	3.3603	6.2175	7.6995
		(0.0000)*	(0.0000)*	(0.0000)*	(0.0000)*	(0.0020)*	(0.0012)*	(0.0000)*	(0.0000)*
	4	6.4765	6.8192	8.0333	8.3788	4.8040	3.7670	7.1142	8.5122
		(0.0000)*	(0.0000)*	(0.0000)*	(0.0000)*	(0.0000)*	(0.0004)*	(0.0000)*	(0.0000)*
	5	6.1511	7.3011	8.5197	8.6193	5.8446	4.1091	7.6548	8.9366
		(0.0000)*	(0.0000)*	(0.0000)*	(0.0000)*	(0.0000)*	(0.0004)*	(0.0000)*	(0.0000)*

Notes: All the BDS test statistics are computed using *EViews* version 4.1. Asymptotically, the computed BDS test statistics, $W_{m,n}(\varepsilon)$ ~N(0,1) under the null of i.i.d. To compensate for smaller sample sizes, this table provides the bootstrapped p-values in parentheses, with 10000 repetitions, generated by *EViews*.
* denotes significant at least at the conventional 5% level.

a trading rule which is able to exploit these detected structure of dependencies. As mentioned in the earlier section, the rejection of the i.i.d. null may be due to linear stochastic systems (AR, MA, ARMA, etc); non-stationarity (regime shift), non-linear stochastic structures (for example, ARCH or GARCH models) and non-linear deterministic structures (such as low dimensional chaos). Alternatively, one can resort to the windowed-test procedure of Hinich and Patterson (1995) to determine whether the dependency structures are persistent enough to be exploitable by investors (see, for example, Ammermann & Patterson, 2003). This remains an avenue for further research.

Another interesting insight from this study is provided by the sub-periods analysis. Specifically, the occurrence of the Asian financial crisis on 1 July 1997 is selected as the break point as we conjecture that the crisis will adversely affect the market's ability to price stocks efficiently, thus preventing stock prices from following a random walk process. The results from Hong Kong Hạng-Seng (HKHS) in particular provide strong support for our conjecture, in which the price behaviour of this market experiences a dramatic change from random walk in the pre-crisis period to non-random during the crisis.

As a whole, the main contribution of this study is methodological, that is re-examining the random walk behaviour of Asian stock markets using a more powerful BDS test. This is crucial because the inferences drawn are based solely on the empirical results of the statistical tests employed. However, there are some issues left unresolved in the present study, which we recommend for further study. First, for the five Asian stock markets which behave consistently in a non-random manner, it would be interesting to investigate the factors that contribute to their divergence from random walk, especially in the period before crisis. Second, the existence of pockets of efficiency in Nikkei, which is quite persistent throughout both sub-periods, remains a puzzle to be solved. Last but not least, especially considering its relevancy to most investors, is to assess whether the underlying patterns of these non-random returns series can be identified and profitably exploited. Thus, this study warrants more extensive work to broaden and enrich the random walk literature of Asian stock markets.

NOTES

1. In this case, it is necessary to first uncover the structure of dependencies in this non-random series. If investors could have profit-

ably operated a trading rule (net of all transactions costs) which exploits those detected dependencies, then it would be at odds with the weak-form efficient market hypothesis.

2. In time series modelling, it is assumed that the movements of a time series are solely explained in terms of its own past and therefore forecasts can be made by extrapolation of the past (Harvey, 1993). The work of time series modelling and forecasting has close connection with technical analysis, which basically involves the study of past price behaviour in order to draw conclusions concerning the direction and magnitude of future price movements.

3. Campbell *et al.* (1997) distinguished between three different versions of the random walk model. Random Walk 1 is the strongest version of the random walk hypothesis and requires independent and identically distributed price changes. Random Walk 2 model assumes independent but not identically distributed price changes. Finally, by relaxing the independence assumption of Random Walk 2 will provide the weakest version of the random walk hypothesis, which the authors refer to as the Random Walk 3 model.

4. The growing popularity of the BDS test has witnessed its incorporation into the commercial statistical package of *EViews* version 4.1.

5. In Grassberger & Procaccia (1983), the correlation integral was introduced as a measure of the frequency with which temporal patterns are repeated in the data. For example, the correlation integral $C(\varepsilon)$ measures the fraction of pairs of points of a time series $\{x_t\}$ that are within a distance of ε from each other.

6. $V_m(\varepsilon)$ can be estimated consistently by $V_{m,n}(\varepsilon)$. For details, refer Brock *et al.* (1987, 1996).

7. The null of i.i.d. implies that $C_{m,n}(\varepsilon) = C_{1,n}(\varepsilon)^m$ but the converse is not true.

8. We thank the reviewer for the suggestion of breaking the sample into sub-periods in order to observe the consistency of the random walk behaviour. Indeed, with the occurrence of the Asian financial crisis on 1 July 1997 as the break point, it has enabled us to make meaningful comparisons and getting much insight into the price

behaviour during the crisis, an area that has not been well-researched in the current literature.

ACKNOWLEDGEMENTS

The authors would like to thank the anonymous referee of the journal for constructive comments that has greatly improved the final version of the paper. The usual disclaimer applies to any remaining errors or omissions.

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